Resource Allocation Algorithm for UAV Aided Symbiotic Radio Communication System

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Abstract

Aiming at the issue of how to improve the system transmission rate in a multiple Internet of things (IoT) device application scenario, we propose the resource allocation algorithm of the symbiotic radio communication system under multiple backscatter devices (BDs) assisted by unmanned aerial vehicle (UAV). We formulate the optimization problem of maximizing BDs' sum rate by jointly optimizing the time allocation, BDs' reflection coefficient and UAV location under constraints of BD's harvested energy, quality of service (QoS) of cellular user and UAV. Since the problem is non-convex, it is difficult to solve directly. Therefore, the iterative algorithm based on block coordinate descent (BCD) method can be adopted, which decomposes the optimization problem into three sub-problems: time allocation, reflection coefficients of BDs and UAV location. For non-convex sub-problems, we utilize the successive convex approximation (SCA) technique to transform it into convex optimization problems, and we prove that the conversion is convex optimization problems. Simulation results show that our proposed algorithm converges fast, and significantly improves the system transmission rate compared with other schemes.

Keywords: Symbiotic radio, Unmanned aerial vehicle, Backscatter, Resource allocation, Energy harvesting

1 Introduction

With the development of IoT applications, large-scale IoT device communication requires huge energy and communication resources. How to ensure effective communication of IoT devices under limited resources is one of the important issues. To solve the problem of short battery life of IoT terminals, making use of energy harvesting technology can extend battery life of these devices [1]. IoT devices can utilize energy from radio frequency (RF) emitters to extend battery life. Ambient backscatter communication (AmBC) technology [2] avoids the use of active RF components, saving energy and reducing costs. Secondly, it can improve the utilization of spectrum resources by using the existing RF signal without allocating new spectrum to its system. As an emerging symbiotic radio technology, it utilizes modulated environmental RF sources (e.g., TV towers, cellular base stations, and Wi-Fi access points [2]) rather than unmodulated dedicated signals to transmit signals through backscatter modulation to complete wireless communication. Since backscatter communication shares spectrum with existing systems, it will cause large interference. Therefore, how to reduce interference and improve system transmission rate through reasonable resource allocation has become a research hotspot [3].

The problem faced by the symbiotic radio communication system is that among the signals received by backscatter receiver, the backscattered signal of BD is much weaker than the signal transmitted by the direct link due to the double channel fading of the backscattered signal, resulting in a small backscatter rate [4]. One of the useful solution can be considered, which is to directly process the received signal at the receiver, and the successive interference cancellation (SIC) technology [1] is one of effective methods. Its basic principle is to first decode the stronger signal in the combined signal, then subtract the signal, and extract the weaker one from the remaining signal. Ref. [5] considered a new symbiotic radio model, cooperative ambient backscatter system. In this system, there is not only a backscatter receiver, but also a primary user, that is, the user served by the RF source. This process is defined as the primary transmission, so the passive backscatter transmission and active primary transmission in one system shares the same spectrum and RF source. In [6] and [7], the system contains multiple BDs, and SIC technology is utilized to decode BD data. The difference is that multiple BDs use the same receiver in [6], and each BD in [7] communicates with an associated cellular user. It is necessary to consider the user association problem and find an optimal strategy to make each BD communicate with the most suitable cellular user. SIC technology is a method to suppress direct interference at receiver. However, whether the strong signal can be perfectly processed is an important factor to be considered in this technology. For different results of processing, it can also affect the transmission rate to a certain extent. The previous [5-7] all assume that the strong signal has been completely removed, but this is not the case in practical applications. The strong signal will have a certain residue

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and cause interference for the weak signal demodulation.

Another effective solution to the problem of limited communication range and low rate caused by double-channel fading in backscatter systems is to substitute the UAV for equipment such as the RF transmitter source or receiver. UAV-aided wireless communication has attracted more and more interest in academia and industry because of its advantages in flexible deployment, high maneuverability and high probability of line of sight (LOS) connection from air to ground. So UAVs have been extensively applied in multifarious scenarios, such as relaying, data gathering, and IoT applications. A UAV-based millimeter-wave (mmWave) relaying network is studied in [8], which the UAVs as relays to assist remote or blocked communication nodes. [9] and [10] both consider that intelligent reflecting surface (IRS) is adopted to assist UAV to improve the system performance. The UAV serves both a ground user and a high-altitude node in [9]. The latter consider UAVs as aerial base stations (ABS) and low-flying ABS along with the IRS. And the UAVs also as ABS in [11] and [12]. The authors both optimized the ABS horizontal positions. Reference [11] proposes the use of K-means and Q-learning assisted 3D ABS Placement and Power allocation algorithm (KQPP) to maximize the system sum capacity. In [12], they handled the problem of optimizing the user sum rate by associating the prioritized users to the deployed emergency ABS.

Furthermore, the UAV can also assist backscatter communication systems. In [13-15], the UAV is utilized as a mobile RF transmitter to provide energy for passive BD. By jointly optimizing the trajectory of the UAV, time slot allocation and BDs' power reflection coefficient in a limited period of flight cycle, the system transmission rate is maximized. The authors of [13] utilized UAV to enhance the communication connection between BD and receiver. According to whether there is a direct connection between the two, it is divided into two cases. The objective is to maximize the capacity of backscatter communication network under different conditions. In [14], the total energy efficiency of all IoT nodes is maximized, and the nodes are wirelessly powered by UAV is maximized. It proposed a new UAV hybrid backscatter communication and Harvest Then Transmit (HTT) communication system that provides RF energy for multiple IoT nodes which are connected to a reader. In [15], a UAV first accessed multiple ground backscatter tags by TDMA and collected data from them, then flew to the coverage area of the terrestrial base station to upload the collected data to the associated base station, and analyzed the average outage probability of the system. In [16], the introduction of multiple UAVs to the backscatter system to cooperate to complete communication was studied, making full use of the flexibility of the UAV, and optimizing its trajectory to achieve the objective of maximizing the total energy efficiency or throughput. Reference [17] has considered the problem of secure backscatter communication system with multiple eavesdroppers assisted by UAV, and the goal is to maximize the secrecy rate of BDs. However, in above scenarios, battery storage capacity of UAV is actually limited. As a RF emission source, its energy consumption is also large, so the power of UAV is a factor to be considered. For this problem, [16-17] and [18] assumed that the power of UAV is always sufficient throughout the communication process of flight, but this is obviously not fully guaranteed in practice. Therefore, in [19], the author considered equipping each UAV with a dedicated charging station, always concerned about whether the UAV's power is sufficient, but the trajectory design of the UAV in the whole system will also be relatively complex. [20] assumed that there is a dedicated RF source, UAV only as a receiver, collecting terrestrial BDs' data, considering the UAV location and time optimization, but did not consider optimizing the reflection coefficients of BD.

In conclusion, [16-20] utilize the UAV as a mobile data receiver symbiotic radio system model is more reasonable. However, the above works utilize a dedicated RF source, which does not share the spectrum and RF source with the existing system, and they require additional spectrum and low spectrum utilization. In this paper, a UAV-aided symbiotic radio communication system is constructed. BDs (passive sensor) utilize the RF signal sent by the base station to cellular user to complete the energy harvesting and backscatter communication, that is, the main transmission system and the backscatter system share the spectrum. At the same time, exploiting the flexible mobility of the UAV as a receiver can not only improve the utilization of spectrum resources, but also solve the problem of low backscatter rate. Under the constraints of energy harvesting by BDs (passive sensor) and QoS of cellular users, a joint optimization algorithm of the time allocation, BDs' reflection coefficient and UAV location is proposed to maximize BDs' sum rate.

Our main contributions are summarized as follows:

1) An UAV-assisted passive sensor data collection system based on symbiotic radio is established. The UAV is acted as a mobile data receiver to collect the information of terrestrial BDs (if there is no special description in this paper, BD means passive sensor). Multiple BDs are randomly distributed within the coverage of the base station. The RF signal received by BD to the base station is divided into two parts. One part is used for energy harvesting for BDs' own circuit consumption, and the other part is used for symbiotic radio technology. The data is sent to the UAV, and the transmission in time division multiple access (TDMA).
2) The optimization problem of BDs' sum rate maximization is constructed under the constraints of QoS of base station cellular users and BD energy harvesting. Since the optimization problem involves multiple variables, and the variables are coupled in the objective function and constraint function, it is complex to solve directly. The BCD method is utilized to decompose the original problem into three sub-problems: time allocation, BD reflection coefficients and UAV location.
3) Sub-problem 1 is a convex optimization problem of linear programming. The CVX is adopted to obtain the optimal time allocation. Sub-problem 2

and sub-problem 3 are non-convex problems. We utilize SCA technology to deal with non-convex functions. The non-convex optimization problem is transformed into a convex optimization problem by employing Taylor's first-order expansion. It is proved that the transformed new problem is convex. Finally, the CVX is adopted to solve the optimal BDs' reflection coefficient and UAV location.

4) The convergence of the proposed algorithm is analyzed by simulation, and the performance of the proposed algorithm is compared with that of [20]. The simulation results indicate that our proposed resource allocation algorithm has faster speed of convergence, and under the same parameter conditions, the performance of the proposed algorithm is obviously better than that of the comparison reference [20], and the system performance is improved by about 28.4%.

The other contents of this paper are as follows: the second part establishes system model and optimization problem of UAV-assisted symbiotic radio system; the third part proposes an iterative algorithm for solving optimization problems. The fourth part simulates and analyzes the algorithm of this paper; the last part summarizes this article.

2 System Model and Problem Formulation

2.1 System Model

The UAV-aided symbiotic radio system model constructed in this paper is shown in Figure 1. $K(K \geq 1)$ BDs are randomly distributed within the range of the base station (BS). An UAV collects all terrestrial BDs information at a fixed altitude $H > 0$ above the ground. The total communication time of the UAV is $T > 0$. The BDs utilize the signal transmitted by the BS to the cellular user for energy harvesting to maintain the circuit operation. At the same time, the information of the BD is backscattered to the UAV by the symbiotic radio technology. The process of BS providing services to cellular users (taking a cellular user as an example) is defined as primary transmission. Passive backscatter transmission in the system shares spectrum with active primary transmission. In the communication process, BD backscatter transmission cause interference to the reception of cellular users, and the direct link of BS to UAV also interfere with its reception. Since the direct link signal is stronger than the backscatter link signal of the double channel fading, for the processing of the UAV received signal, we employ the SIC technology to remove the interference signal of the direct link.

TDMA is used to communicate between UAV and BD, as shown in Figure 2. Assume that the total communication time is divided into $N > 0$ time slots on average, $T = N\delta$, and the location of UAV on the 2D horizontal plane of the time τ_n, $n \in \{1, 2, ..., n, ..., N\}$ is denoted by $q_n = (x_n, y_n)$. The UAV is hovering over the location q_n during each time period τ_n, when terrestrial BDs communicate with the UAV via TDMA, the length of time allocated to BDk is denoted by $\tau_{k,n}$, $k \in \{1, 2, ..., k, ..., K\}$.

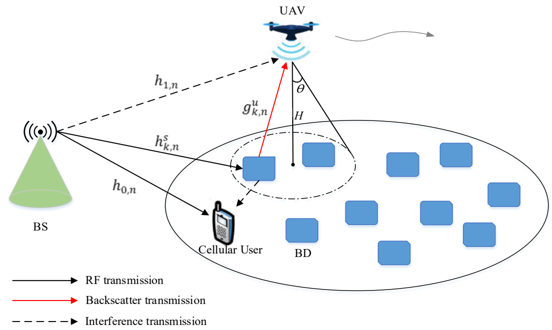

Figure 1. UAV-aided symbiotic radio system model

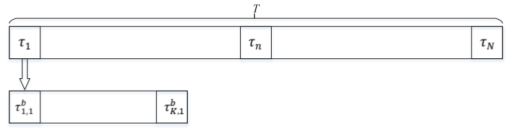

Figure 2. Time allocation scheme

When the UAV is hovering, not all BDs can communicate with it. Only BDs within the UAV communication range can complete backscatter communication. We give $a_{k,n}$ to represent the 0-1 indication coefficient of whether BD can backscatter. When the BDk is within the UAV communication range in time, i.e., the horizontal distance between UAV and BDk is less than or equal to the communication radius of UAV, the expression is given by

$$a_{k,n} = \begin{cases} 1, \|q_n - w_k\| \leq r \\ 0, \|q_n - w_k\| > r \end{cases} \tag{1}$$

where $w_k = (w_k^x, w_k^y)$ represents the 2D location of BDk, $r = H\tan\theta$ is the UAV communication range, θ is the effective illumination angle of UAV, and the backscattering time allocated by BDk is denoted by $\tau^b_{k,n} = a_{k,n}\tau_{k,n}$.

We assume that Channel State Information (CSI) is known. The channel gains from BS to cellular users, from BS to BDk and from BD to cellular users are denoted by $h_{0,n}$, $h^s_{k,n}$, $g^l_{k,n}$, respectively. We adopt that the three terrestrial channels consider both large-scale and small-scale fading [14], namely:

$$h_{0,n} = \xi_0 \left(d_{0,n}\right)^{-\alpha} \left\|\mu_{0,n}\right\|^2 \tag{2}$$

$$h^s_{k,n} = \xi_0 \left(d^s_{k,n}\right)^{-\alpha} \left\|\mu^s_{k,n}\right\|^2 \tag{3}$$

$$g^l_{k,n} = \xi_0 \left(d^l_{k,n}\right)^{-\alpha} \left\|\mu^l_{k,n}\right\|^2 \tag{4}$$

where $d_{0,n} = \sqrt{\|q_L - q_B\|^2}$, $d^s_{k,n} = \sqrt{\|q_B - w_k\|^2}$ and $d^l_{k,n} = \sqrt{\|q_L - w_k\|^2}$ represent the distance between BS and cellular user, the distance between BS and BDk and the distance between BDk and cellular user, q_B and q_L represent the 2D location of BS and cellular user, $\mu_{0,n}$, $\mu^s_{k,n}$ and $\mu^l_{k,n}$ represent respectively the small-scale fading part [14], ξ_0 denotes the channel power gain at a reference distance of $d_0 = 1m$, α denotes the path loss exponent.

The channel gains from BS to UAV and from BDk to UAV are expressed as $h_{1,n}$, $g^u_{k,n}$, respectively. The communication between BS and UAV is assumed to be a Line of Sight (LOS) channel, and only large-scale fading is considered. We have

$$h_{1,n} = \xi_0 \left(d_{1,n}\right)^{-2} \tag{5}$$

$$g^u_{k,n} = \xi_0 \left(d^u_{k,n}\right)^{-2} \tag{6}$$

where $d_{1,n}$, $d^u_{k,n}$ respectively denote the distance between BS and UAV, the distance between UAV and BDk, $d_{1,n} = \sqrt{\|q_n - q_B\|^2 + H^2}$, $d^u_{k,n} = \sqrt{\|q_n - w_k\|^2 + H^2}$.

Let us denote S_n as the primary transmission signal sent by the BS at τ_n, $E[\|S_n\|^2] = 1$, then BDk received signal from the BS can be written as

$$y_{b,k}\left(n\right) = \sqrt{Ph^s_{k,n}} S_n \tag{7}$$

where P represents the BS's transmit power.

When BDk is located in the communication range of UAV, the received signal of BDk is split into two parts. One is utilized to support the backscatter transmission of BDk, and the remaining of the energy is collected by BDk for its circuit consumption. For the duration of τ_n, if BDk does not carry out backscatter communication, let $a_{k,n} = 0$, and all signals received by BD are used for energy harvesting; when BDk performs backscatter communication and energy harvesting simultaneously, $a_{k,n} = 1$. Let us denote $\beta_{k,n}$ as the reflection coefficient of BDk, $0 \le \beta_{k,n} \le \beta_{\max}$, $\beta_{\max}(0 < \beta_{\max} < 1)$ [21] is the maximum reflection coefficient that can be achieved in practical applications. Thus, the total energy harvested by BDk during the communication time T is represented as

$$\begin{aligned} E_k &= \sum_{n=1}^{N} \eta_k \left[\tau^b_{k,n} P\left(1 - \beta_{k,n}\right) h^s_{k,n} + Ph^s_{k,n} \left(T/N - \tau^b_{k,n} \right) \right] \\ &= \sum_{n=1}^{N} \eta_k Ph^s_{k,n} \left(T/N - \tau^b_{k,n} \beta_{k,n} \right) \end{aligned} \tag{8}$$

where η_k is the energy harvesting efficiency of BDk. We denote $C_{k,n}$ represents BD's own signal at time slot τ_n, $E[\|C_n\|^2] = 1$. Thus the transmitted signal of BDk backscatter the UAV is given by

$$y'_{k,n}\left(n\right) = a_{k,n} \sqrt{P\beta_{k,n} h^s_{k,n}} S_n C_{k,n} \tag{9}$$

For cellular user, the backscattered signal of BDk will cause interference to it, so the received signal of cellular user at time slot τ_n can be expressed as

$$y_l\left(n\right) = \sqrt{Ph_{0,n}} S_n + \sum_{k=1}^{K} y'_{k,n}\left(n\right) \sqrt{g^l_{k,n}} + Z^l_n \tag{10}$$

where $Z^l_n \sim (0, \sigma^2_l)$ donates the additive white Gaussian noise (AWGN) at cellular user. Thus, the signal to interference plus noise ratio (SINR) at cellular user are represented as

$$\gamma_s\left(n\right) = \frac{Ph_{0,n}}{\sum_{k=1}^{K} a_{k,n} P\beta_{k,n} h^s_{k,n} g^l_{k,n} + \sigma^2_l} \tag{11}$$

where the first item of the denominator is the interference caused by backscattered BDs to the primary transmission, then the transmission rate of primary transmission at time slot τ_n can be calculated as

$$R_s\left(n\right) = W \log_2\left(1 + \gamma_s\left(n\right)\right) \tag{12}$$

where W denotes the system channel bandwidth.

The received signal of UAV at time slot τ_n is given by

$$y_{u,k}\left(n\right) = \sqrt{Ph_{1,n}} S_n + y'_{k,n}\left(n\right) \sqrt{g^u_{k,n}} + Z^u_n \tag{13}$$

where $Z^u_n \sim (0, \sigma^2_u)$ represents the AWGN at UAV. The first item on the right side of the equation is the direct link interference of BS to UAV and the interfering signal is stronger than the backscatter link signal due to the double channel fading. In order to decode the signal $C_{k,n}$ of BDk, the strong signal $\sqrt{Ph_{1,n}} S_n$ needs to be removed by SIC technology. In practical applications, due to hardware limitations, channel estimation errors, low signal quality and other reasons, there may be decoding errors of interference signals [22]. Therefore, there may be residual signal interference after SIC, called imperfect SIC. So the signal-noise ratio (SNR) of the signal $C_{k,n}$ decoding BDk at UAV is expressed as

$$\gamma_{c,k}\left(n\right) = \frac{\psi P a_{k,n} \beta_{k,n} h^s_{k,n} g^u_{k,n}}{\sigma^2_u} \tag{14}$$

where $\psi(-60dB \le \psi \le -20dB)$ [14] denotes the imperfect SIC coefficient.

The backscattered transmission rate of BDk at time slot τ_n can be expressed as

$$R_{c,k}\left(n\right)=\frac{\tau_{k,n}^{b}}{\delta}W\log_2\left(1+\gamma_{c,k}\left(n\right)\right) \tag{15}$$

2.2 Problem Formulation

The objective of this paper is to maximize the sum rate of all BDs by jointly optimizing time allocation $\tau_n^b=[\tau_{1,n}^b, ..., \tau_{K,n}^b]$ BDs' reflection coefficients $\beta_n=[\beta_{1,n}, ..., \beta_{K,n}]$ and UAV location q_n, while meeting the minimum rate of each BD and the QoS requirements of cellular user. The sum rate of all BDs is expressed as

$$R_{sum}=\sum_{n=1}^{N}\sum_{k=1}^{K}R_{c,k}\left(n\right) \tag{16}$$

Accordingly, the problem is formulated as

$$\begin{aligned} P1:\quad & \max_{\{\tau_n^b,\beta_n,q_n\}} R_{sum} \\ s.t.\ & \text{C1: } \frac{T}{N}=\sum_{k=1}^{K}\tau_{k,n}^b,\ \ \tau_{k,n}^b\geq 0,\forall k,\forall n \\ & \text{C2: } 0\leq \beta_{k,n}\leq \beta_{\max},\forall k,\forall n \\ & \text{C3: } \sum_{n=1}^{N}R_s(n)\geq R_{\min}^s \\ & \text{C4: } \sum_{n=1}^{N}R_{c,k}\left(n\right)\geq R_{\min}^b,\forall k \\ & \text{C5: } E_0+E_k\geq E_{\min},\forall k \\ & \text{C6: } \frac{\left\|q_n-q_{n-1}\right\|}{\delta}\leq V_{\max},\forall n \\ & \text{C7: } q_0=q_T \end{aligned} \tag{17}$$

where C1 specifies the constrain of total communication time and the value range of BDs backscatter time; C2 represents the constrain of the reflection coefficient, and $\beta_{\max}$ denote the maximum reflection coefficient; $R_{\min}^s$ in C3 denotes the minimum requirements of the primary transmission rate are guaranteed to meet the QoS of cellular user; C4 guarantees the minimum transmission rate $R_{\min}^b$ for each BD; C5 is the causal relationship of energy, each BD is required to consume cannot exceed the sum of its initial energy E_0 and the collected energy E_k during transmission, and $E_{\min}$ represents the minimum energy requirement for each BD circuit to work; $V_{\max}$ in C6 represents the maximum speed of the UAV; In C7 we assume the UAV starts at an initial location and flies back to the initial location finally.

Since there are many variables τ_n^b, β_n and q_n coupling in the objective function and constraint function, the problem is non-convex for variables β_n and q_n, and cannot be directly solved by commonly convex optimization method. In order to make the problem easier to deal with, we use BCD method, which alternately solves the variables by optimizing a variable while keeping the remaining variables fixed in each iteration.

3 Problem Solution

In order to solve the proposed optimization problem $P1$, we decompose the original problem into three sub-problems: time allocation, BDs' reflection coefficient and UAV location based on BCD method. The basic algorithmic strategy of BCD methods is known in the literature [23]. As working with all the variables of an optimization problem at each iteration may be inconvenient, difficult or impossible for any or all of the reasons mentioned above, the variables are partitioned into manageable blocks, with each iteration focused on updating a single block only, the remaining blocks being fixed [24]. So we use BCD method to divide the original optimization problem into three blocks. The first sub-problem is a standard linear programming (LP), which is a convex optimization problem. The latter two sub-problems are non-convex about variables, which are processed by SCA technology. The Taylor expansion of the function is used to approximate the non-convex function, and the non-convex optimization problem is transformed into a convex problem. It is proved that the new problem after transformation is convex. Finally, the CVX toolbox is utilized to solve the problem to obtain the optimal BDs' reflection coefficient and UAV location.

3.1 Time Allocation Optimization

For sub-problem 1, given the BDs' reflection coefficient β_n and the UAV location q_n, by optimizing the time allocation to maximize the sum rate of all BDs, then sub-problem 1 can be described as

$$\begin{aligned} P2:\quad & \max_{\{\tau_n^b\}} R_{sum} \\ s.t.\ & \text{C1: } \frac{T}{N}=\sum_{k=1}^{K}\tau_{k,n}^b,\ \ \tau_{k,n}^b\geq 0,\forall k,\forall n \\ & \text{C4: } \sum_{n=1}^{N}R_{c,k}\left(n\right)\geq R_{\min}^b,\forall k \\ & \text{C5: } E_0+E_k\geq E_{\min},\forall k \end{aligned} \tag{18}$$

Obviously, the objective function in $P2$ and the constraint functions of C4 and C5 are linear with respect to the variable $\tau_{k,n}^b$, so the problem is a standard LP problem, which can be solved by the commonly used optimization methods. In this paper, the CVX toolbox is utilized to solve the problem directly.

3.2 Reflection Coefficient Optimization

For sub-problem 2, given the time allocation length τ_n^b and the UAV location q_n, by optimizing the reflection coefficient to maximize the sum rate of all BDs, then sub-problem 2 can be described as:

$$
\begin{aligned}
P3:\quad & \max_{\{\beta_n\}} R_{sum} \\
s.t.\ & \text{C2: } 0 \le \beta_{k,n} \le \beta_{\max}, \forall k, \forall n \\
& \text{C3: } \sum_{n=1}^{N} R_s(n) \ge R^s_{\min} \\
& \text{C4: } \sum_{n=1}^{N} R_{c,k}(n) \ge R^b_{\min}, \forall k \\
& \text{C5: } E_0 + E_k \ge E_{\min}, \forall k
\end{aligned} \tag{19}
$$

The objective function R_{sum} and the constraint function $R_{c,k}(n)$ are concave functions with respect to β_n, but the constraint function of C3 is a non-concave function about β_n, so $P3$ is a non-convex optimization problem. In order to solve the non-convexity of this problem, the constraint function is re-represented as

$$
\begin{aligned}
R_s(n) &= W\log_2\left(1+\frac{Ph_{0,n}}{\sum_{k=1}^{K} a_{k,n}P\beta_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2}\right) \\
&= W\log_2\left(Ph_{0,n}+\sum_{k=1}^{K} a_{k,n}P\beta_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right) \\
&\quad -W\log_2\left(\sum_{k=1}^{K} a_{k,n}P\beta_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right)
\end{aligned} \tag{20}
$$

According to (20), the first logarithmic function is a concave function with respect to β_n, while the second term is a convex function with respect to β_n, which makes the constraint function neither convex nor concave. Therefore, SCA technology can be used to convert (20) into a concave function so that $P3$ can be solved. The basic idea of SCA technology is to utilize the lower bound of the original function instead of successive approximation as a concave function in each iteration process, i.e., to deal with the function is to find a lower bound function approximation of it and bring it into the optimization problem. Since the first-order Taylor expansion of any convex function at any point can be its global lower bound, it is approximated by the first-order Taylor expansion of the function at an iteration point. Thus, the first-order Taylor expansion of the constraint function (20) at $\beta^t_{k,n}$ is given by

$$
\begin{aligned}
R_s(n) &\ge R^{lb}_s(n) \\
&= W\log_2\left(Ph_{0,n}+\sum_{k=1}^{K} a_{k,n}P\beta_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right) \\
&\quad -W\log_2\left(\sum_{k=1}^{K} a_{k,n}P\beta^t_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right) \\
&\quad -W\frac{\sum_{k=1}^{K} a_{k,n}Ph^s_{k,n}g^l_{k,n}(\beta_{k,n}-\beta^t_{k,n})}{\ln 2\left(\sum_{k=1}^{K} a_{k,n}P\beta^t_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right)}
\end{aligned} \tag{21}
$$

So we obtain the second-order derivative of $R^{lb}_s(n)$

$$
\frac{\partial R^{lb}_s(n)}{\partial \beta_{k,n}{}^2} = -\frac{W\left(\sum_{k=1}^{K} a_{k,n}P\beta_{k,n}h^s_{k,n}g^l_{k,n}\right)^2}{\ln 2\left(Ph_{0,n}+\sum_{k=1}^{K} a_{k,n}P\beta^t_{k,n}h^s_{k,n}g^l_{k,n}+\sigma_l^2\right)^2} \le 0 \tag{22}
$$

Thus, using the properties of convex functions, we know the function $R^{lb}_s(n)$ is concave. Then $P3$ can be transformed into a new convex optimization problem.

$$
\begin{aligned}
P4:\quad & \max_{\{\beta_n\}} R_{sum} \\
s.t.\ & \text{C2,C4,C5} \\
& \text{C3}'\text{:} \sum_{n=1}^{N} R^{lb}_s(n) \ge R^s_{\min}
\end{aligned} \tag{23}
$$

The BDs' reflection coefficient sub-problem is transformed into a convex optimization problem, which can be effectively solved by CVX toolbox.

3.3 UAV Location Optimization

For sub-problem 3, given the time allocation length τ^b_n and the reflection coefficient β_n, by optimizing the UAV location to maximize the sum rate of all BDs, then sub-problem 3 can be described as

$$
\begin{aligned}
P5:\quad & \max_{\{q_n\}} R_{sum} = \sum_{n=1}^{N}\sum_{k=1}^{K}\frac{W\tau^b_{k,n}}{\delta}\log_2\left(1+\frac{\psi P a_{k,n}\beta_{k,n}h^s_{k,n}\xi_0}{\sigma_u^2\left(\left\|q_n-w_k\right\|^2+H^2\right)}\right) \\
& s.t.\ \text{C4: } \sum_{n=1}^{N} R_{c,k}(n) = \\
& \sum_{n=1}^{N}\frac{\tau^b_{k,n}}{\delta}W\log_2\left(1+\frac{\psi P a_{k,n}\beta_{k,n}h^s_{k,n}\xi_0}{\sigma_u^2\left(\left\|q_n-w_k\right\|^2+H^2\right)}\right) \ge R^b_{\min}, \forall k \\
& \text{C6: } \frac{\left\|q_n-q_{n-1}\right\|}{\delta} \le V_{\max}, \forall n \\
& \text{C7: } q_0 = q_T
\end{aligned} \tag{24}
$$

$P5$ is also a non-convex optimization problem about optimization variables. The objective function and C4 constraint function in $P5$ are not concave functions with respect to variable q_n. Similarly, we also use SCA technology to deal with non-convex problem, and find the lower bound function to approximate it as a concave function. Since the function uses the norm and square operation for q_n, it is relatively complicated to directly expand the Taylor section. Therefore, a slack variable s is first introduced to simplify the process, i.e. $U_n = (U_{1,n}, U_{2,n}, ..., U_{K,n})$. Then the objective function can be re-expressed as

$$R_{sum}=\sum_{n=1}^{N}\sum_{k=1}^{K}\frac{\tau_{k,n}^{b}}{\delta}W\log_2\left(1+\frac{\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0}{\sigma_u^2\left(U_{k,n}+H^2\right)}\right) \quad \textbf{(25)}$$

Define a function $f(U)=A\log_2\left(1+\frac{C}{B(U+H^2)}\right)$, where A, B, C are nonnegative constants, then the Taylor section expansion of the function at $U_0\geq 0$ is given by

$$f(U)\geq A\log_2\left(1+\frac{C}{B(U_0+H^2)}\right)-\frac{A\left(U-U_0\right)}{\ln 2\left(1+\frac{B(U_0+H^2)}{C}\right)\left(U_0+H^2\right)} \quad \textbf{(26)}$$

By taking $A=\frac{\tau_{k,n}^{b}}{\delta}W$, $B=\sigma_u^2$, $C=\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0$, $U=U_{k,n}$, $U_0=U_{k,n}^{t}$ into (26), the Taylor section expansion of R_{sum} at $U_{k,n}{}^{t}=\left\|q_n{}^{t}-w_k\right\|^2$ is given by

$$R_{sum}\geq R_{sum}^{lb}=\sum_{n=1}^{N}\sum_{k=1}^{K}\left[\frac{\tau_{k,n}^{b}}{\delta}W\log_2\left(1+\frac{\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0}{\sigma_u^2\left(U_{k,n}^{t}+H^2\right)}\right)-\frac{\frac{\tau_{k,n}^{b}}{\delta}W\log_2 e\left(U_{k,n}-U_{k,n}^{t}\right)}{\left(1+\frac{\sigma_u^2\left(U_{k,n}^{t}+H^2\right)}{\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0}\right)\left(U_{k,n}^{t}+H^2\right)}\right] \quad \textbf{(27)}$$

For $U_{k,n}=\left\|q_n-w_k\right\|^2=\left(x_n-w_k^x\right)^2+\left(y_n-w_k^y\right)^2$, the second-order derivative of R_{sum}^{lb} as follows

$$\frac{\partial R_{sum}^{lb}}{\partial x_n{}^2}=\frac{\partial R_{sum}^{lb}}{\partial y_n{}^2}=-\sum_{n=1}^{N}\sum_{k=1}^{K}\frac{2\tau_{k,n}^{b}}{\delta}W\log_2 e\leq 0 \quad \textbf{(28)}$$

$$\frac{\partial R_{sum}^{lb}}{\partial x_n\partial y_n}=0 \quad \textbf{(29)}$$

According to the properties of concave functions, (28) and (29) can prove that R_{sum}^{lb} is a concave function with respect to q_n.

Similarly, for the non-convex constraint function C4 in $P5$, we can get

$$\sum_{n=1}^{N}R_{c,k}\left(n\right)\geq\sum_{n=1}^{N}R_{c,k}^{lb}=\sum_{n=1}^{N}\left[\frac{\tau_{k,n}^{b}}{\delta}W\log_2\left(1+\frac{\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0}{\sigma_u^2\left(U_{k,n}^{t}+H^2\right)}\right)-\frac{\frac{\tau_{k,n}^{b}}{\delta}W\log_2 e\left(U_{k,n}-U_{k,n}^{t}\right)}{\left(1+\frac{\sigma_u^2\left(U_{k,n}^{t}+H^2\right)}{\psi Pa_{k,n}\beta_{k,n}h_{k,n}^{s}\xi_0}\right)\left(U_{k,n}^{t}+H^2\right)}\right] \quad \textbf{(30)}$$

The second-order derivative of $R_{c,k}^{lb}$ with respect to x_n and y_n can be calculated as

$$\frac{\partial R_{c,k}^{lb}}{\partial x_n{}^2}=\frac{\partial R_{c,k}^{lb}}{\partial y_n{}^2}=-\frac{2\tau_{k,n}^{b}}{\delta}W\log_2 e\leq 0 \quad \textbf{(31)}$$

$$\frac{\partial R_{c,k}^{lb}}{\partial x_n\partial y_n}=0 \quad \textbf{(32)}$$

According to the properties of concave functions, (31) and (32) can prove that $R_{c,k}^{lb}$ is a concave function with respect to q_n.

By replacing the objective function and constraint function in $P5$ with their lower bounds, the new convex problem can be written as

$$\begin{aligned} P6:\quad & \max_{\{q_n,S_n\}} R_{sum}^{lb} \\ & s.t.\ \sum_{n=1}^{N}R_{c,k}^{lb}\geq R_{\min}^{b} \\ & \text{C6,C7} \end{aligned} \quad \textbf{(33)}$$

Problem $P6$ is convex and can be efficiently solved by CVX toolbox.

3.4 Optimization Algorithm Steps

We use the BCD-based iterative algorithm to decompose the original problem into three sub-problems: time allocation, BDs' reflection coefficient and UAV location optimization. The optimal solution is obtained by alternating iteration, and the specific steps are shown in Algorithm 1. In the j ($j\geq 0$)th iteration, the time allocation, BDs' reflection coefficient and the location of the UAV are expressed as τ_n^j, β_n^j, q_n^j respectively. Through continuous optimization iteration, the objection value and BDs' sum rate are increasing. When the difference between the objective function values obtained by the two iterations is less than a small threshold ε, the algorithm converges.

Algorithm 1. BCD-based iterative algorithm

Input: BS's transmit power P, number of BDs K, energy harvesting efficiency η_k etc.

Output: optimal time allocation τ^*_n, BDs' reflection coefficient β^*_n, UAV location q^*_n.

1: **Initialize:** $j: = 0$, ε;

2: **repeat**

3: Initialize β^j_n, q^j_n, solve linear programming problem $P2$ by CVX, and obtain optimal time allocation;

4: The lower bound of (20) in (21) is brought into $P3$, which is transformed into the convex $P4$. According to τ^*_n and q^j_n obtained in step 3, solve $P4$ by CVX to obtain β^*_n;

5: The objective function and constraint function in the non-convex problem $P5$ are replaced by (26) and (30), and

transformed into $P6$. According to τ^*_n obtained in step 3 and β^*_n obtained in step 4, solve $P6$ by CVX to obtain q^*_n;

6: Update $j: = j + 1$, $\tau^j_n = \tau^*_n$, $\beta^j_n = \beta^*_n$, $q^j_n = q^*_n$;

7: **until** The increase of the objective value R^{lb}_{sum} between iterations is smaller than ε.

4 Numerical Result

We utilize MATLAB to simulate and verify the proposed optimization algorithm. Firstly, the convergence of the proposed algorithm is proved. Secondly, the relationship between the number of BD and its transmission rate is analyzed, and the influence of different parameters, including BS transmit power, BDs' reflection coefficient threshold, and path loss exponent, on BD average transmission rate is analyzed. It is assumed that all BDs are randomly distributed in BS coverage of $20\times20m^2$, the interval on the coordinate system is $-10m\sim10m$, the center location is [0,0], the horizontal location of BS and cellular user are set as $q_B = [-15m, 0]$, and $q_L = [-3m, 5m]$. The altitude of UAV is fixed at $H = 5m$, and its maximum flight speed is $V_{\max} = 10m/s$. The other fixed system parameter values are listed in Table 1 [14, 16-17] and [20].

Table 1. Simulation parameters

Parameter	Value
Number of BD K	20
Number of time slots N	25
Total communication Time T / s	40
BS's transmit power P / W	1
Channel bandwidth W / MHz	10
AWGN power $\sigma^2_l = \sigma^2_u / dBm$	−144
Maximum reflection coefficient $\beta_{\max}$	0.9
Path loss exponent α	3
Energy harvesting efficiency η_k	0.5
Cellar user's minimum transmission rate requirement $R_m(bit / s)$	10^5
Imperfect Sic coefficient ψ / dB	−40

Figure 3 illustrates the convergence of BD's average transmission rate obtained by our proposed algorithm under different transmit power of BS. From the figure, the proposed algorithm based on BCD converges to the optimal value after the third iteration, which proves that the convergence speed of the algorithm is fast. Where BS transmit powers are $1W$, $3W$, $5W$, it can be obviously found that the greater the transmit power, the greater the final convergence of the optimal value. This is due to the increase in BS's transmit power, BD received power is greater, the better the backscatter performance, so the average BD transmission rate rise gradually.

Figure 4 compares the performance of the proposed algorithm with the algorithm in [20], the fixed UAV location and equal time division algorithm. It can be observed from the figure that the average transmission rate of BD decreases with the increase of the number of BD, and the BD's average transmission rate performance of the proposed algorithm is significantly better than that of the comparison [20]. Firstly, although the algorithm in [20] optimizes the location of the UAV, the reflection coefficients of BD are not optimized, and our proposed algorithm optimizes both parameters. Secondly, our time allocation scheme is also different from that in [20]. Because the latter assumes that the passive BD has no initial energy, it is necessary to allocate an additional period of time to perform energy harvesting first to keep the circuit work, and the BD is in sleep state without backscatter. This paper assumes that the BD has a given initial energy and completes the energy harvesting work without backscatter. In the same UAV communication time, compared with [20], the backscatter communication time allocated for BD in our proposed scheme is longer, which makes the average transmission rate of BD larger, so the system performance of proposed algorithm is better than [20]. In addition, the UAV location fixing and equal time division are compared as two benchmark schemes. Obviously, the performance of these two schemes is worse than that of the proposed algorithm.

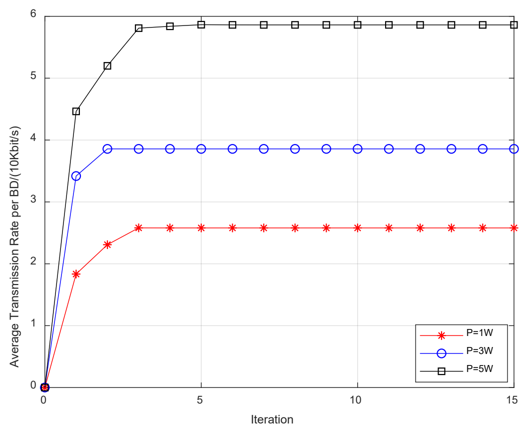

Figure 3. Convergence performance of proposed algorithm under different transmit power

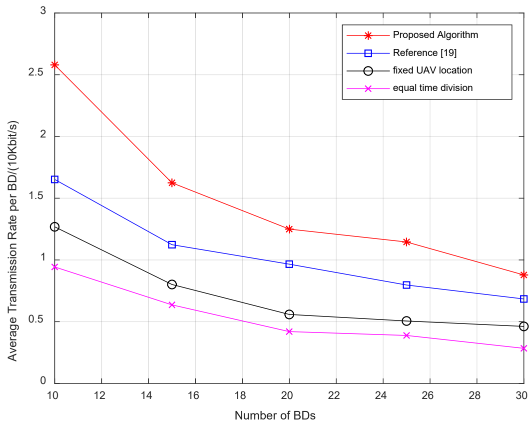

Figure 4. The performance comparison between proposed algorithm and other algorithms

In Figure 5, we compare the impact of the number of BDs on the BD average transmission rate versus different BS's transmit power. The number of BDs is 10, 15, 20, 25 and 30, respectively. As can be plotted from Figure 5 with the increase in the number of BDs, BD's average transmission rate is decreasing. At the same transmit power and total communication time, as the number of BDs increases, the number of backscattered BDs also increases, so the time allocated to each BD for backscatter communication becomes shorter, so the average backscatter transmission rate decreases. In addition, the BD's average transmission rate increases as the transmit power increases under the number of BDs is fixed. This is because when the transmit power increases, BD obtains more power to complete backscatter communication, making its system performance better.

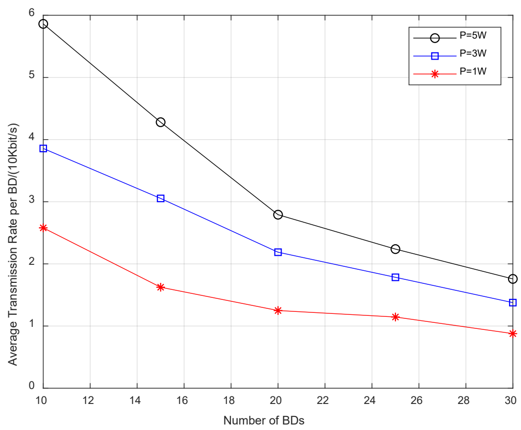

Figure 5. BD's average transmission rate versus number of BDs

Figure 6 shows the effect of different maximum reflection coefficient on the average transmission rate of BD. The maximum reflection coefficient of BD set as $\beta_{\max} = 0.9$, $\beta_{\max} = 0.8$, $\beta_{\max} = 0.7$ respectively. It can be observed from the figure that the larger the maximum reflection coefficient, the better the transmission rate of BD. This is because the maximum reflection coefficient threshold increases, BDs' reflection coefficient can be optimized to get a greater value, i.e., for the backscattering part of the power will become more. Therefore, the average transmission rate of BD will increase.

Figure 7 illustrates the effect of path loss exponent on the average transmission rate of BD. The path loss exponents are $\alpha = 2.5$, $\alpha = 3$ and $\alpha = 3.5$ respectively. It can be plotted from the diagram that the average transmission rate of BD decreases with the increase of path loss exponent. The reason is that when the path loss exponent increases, the channel gain between BS and BD decreases, and BD needs more power to complete the backscatter with the same BS's transmit power and other parameters fixed, so the average transmission rate of the BD will also decrease.

Figure 8 illustrates the effect of incomplete SIC coefficients on the average transmission rate of BD, where the imperfect SIC coefficients are taken as $\psi = -40dB$, $-35dB$ and $-30dB$. From the figure, we can observe that the average transmission rate of BD increases with the increase of ψ, because the larger ψ, the less errors occur in the SIC process, the smaller the residual interference generated by the strong signal to the weak signal, and the BD transmission rate increases.

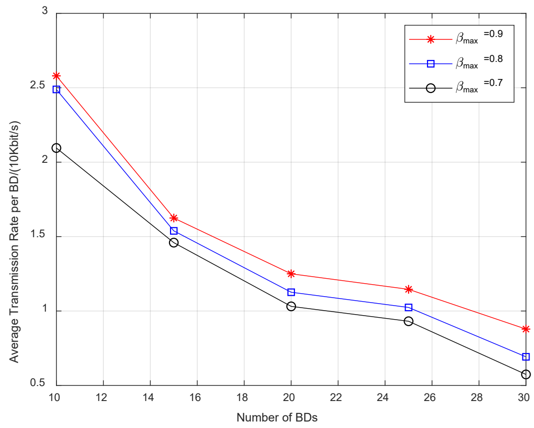

Figure 6. BD's average transmission rate performance with respect to the maximum value of different reflection coefficients

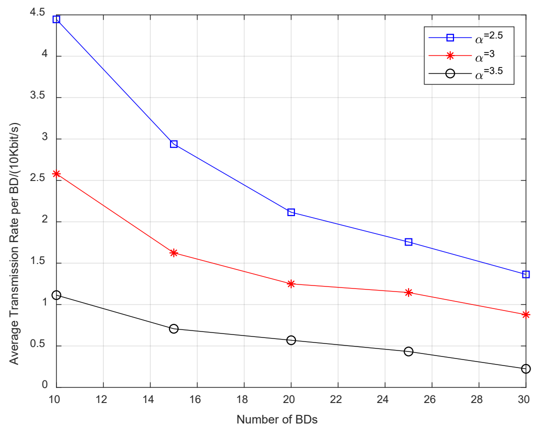

Figure 7. BD's average transmission rate performance with respect to different path loss exponents

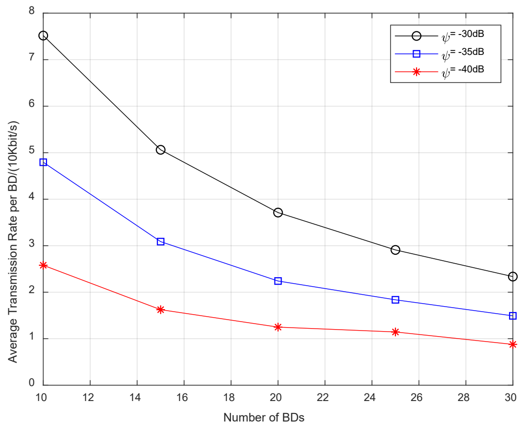

Figure 8. BD's average transmission rate performance with respect to different imperfect SIC coefficients

We also analysis the impact of the location of UAV under our proposed algorithm in Figure 9. We plot the average transmission rate of per BD for UAV altitudes from 3m to 10m, where it is apparent the optimal average rate under different number of BDs is in the height of 5m. We also notice that the average transmission rate decrease when the height of UAV increases because its channel fading also increase with distance. And when the height of UAV too low, the communication range of UAV also decreases. So it leads to the transmission rate of BD dropping.

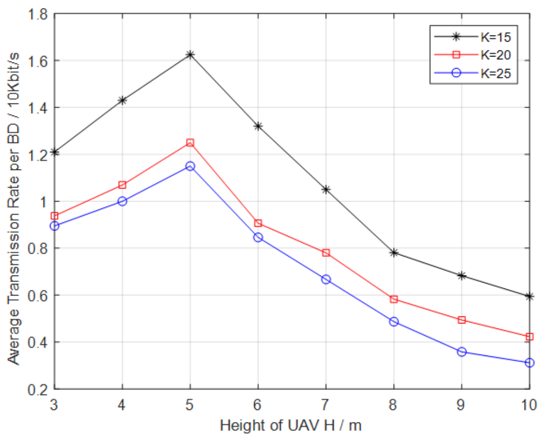

Figure 9. BD's average transmission rate performance with respect to different height of UAV

5 Conclusion

In this paper, the UAV-assisted passive sensor data collection system based on symbiotic radio is studied. The difference between the UAV-assisted backscatter communication system and the general UAV-assisted backscatter communication system is that we don't need to use a special RF source, and establishes a symbiotic radio system. Considering that the BS serves the cellular user, BD utilizes the ambient backscatter technology to collect the energy in the information transmitted by BS to the cellular user to keep its own circuit work and backscatter communication, so the primary transmission and backscatter transmission share the RF source and spectrum, do not occupy the additional spectrum, and improve the utilization of spectrum resources. By jointly optimizing the time allocation, BDs' reflection coefficient and UAV location, our objective is to maximize BDs' sum rate by the constraints of BD energy harvesting, minimum backscatter transmission rate and QoS guarantee of cellular user. Since the established optimization problem is non-convex and complex to be solved directly by general methods, we propose an iterative algorithm based on BCD. The BCD method is used to decompose the original problem into three sub-problems: time allocation, BDs' reflection coefficient and UAV location. The SCA technology is used to transform the non-convex problem into a convex optimization problem, and we solve the transformed convex optimization problem by CVX toolbox. Simulation results demonstrate that our proposed algorithm converges fast, and the system performance is optimal compared with other algorithm schemes. In the future work, the symbiotic radio scenario of multiple UAVs can be further considered, in which the interference between multiple UAVs and BD and trajectory design of UAVs will become the main difficulties of research.

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